



Artificial Intelligence for Financial Inclusion.

**Alternative Data and Risk
Prediction.**

**Graph Databases: A key to
addressing Financial Services
challenges.**

I - Introduction, Definitions

- **Credit Scoring**
 - **Traditional methods**
 - **Credit Bureau**
 - **Alternative Data**
 - **Unbanked population**
 - **Smartphone and Social Networks : A gold mine?**

II - Methods

- **Payment Default (PD) & Risk Prediction**
- **Algorithms selection overview:**
 - **Naive**
 - **SVM**
 - **Random Forest**
 - **Extreme and Light Gradient Boosting**
 - **Deep Learning**

App I : Why and When XGB is better than DP

III - Graph Database - Neo4J

- **Introduction**
 - **Difference with other databases?**
 - **Why is it useful?**
- **Neo4j**
 - **Structure**
 - **Cypher language**
 - **Graph Algorithms**
- **Graph DB at Carbon**

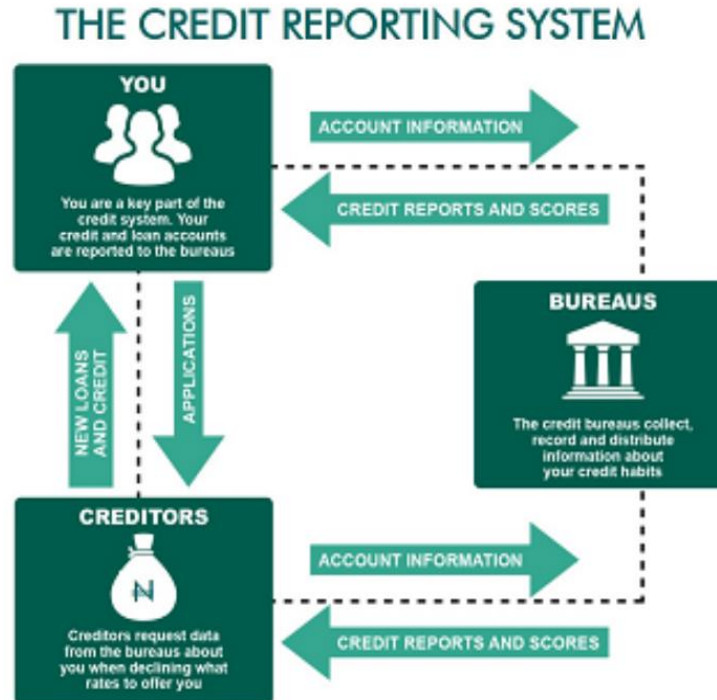
IV - Carbon use cases



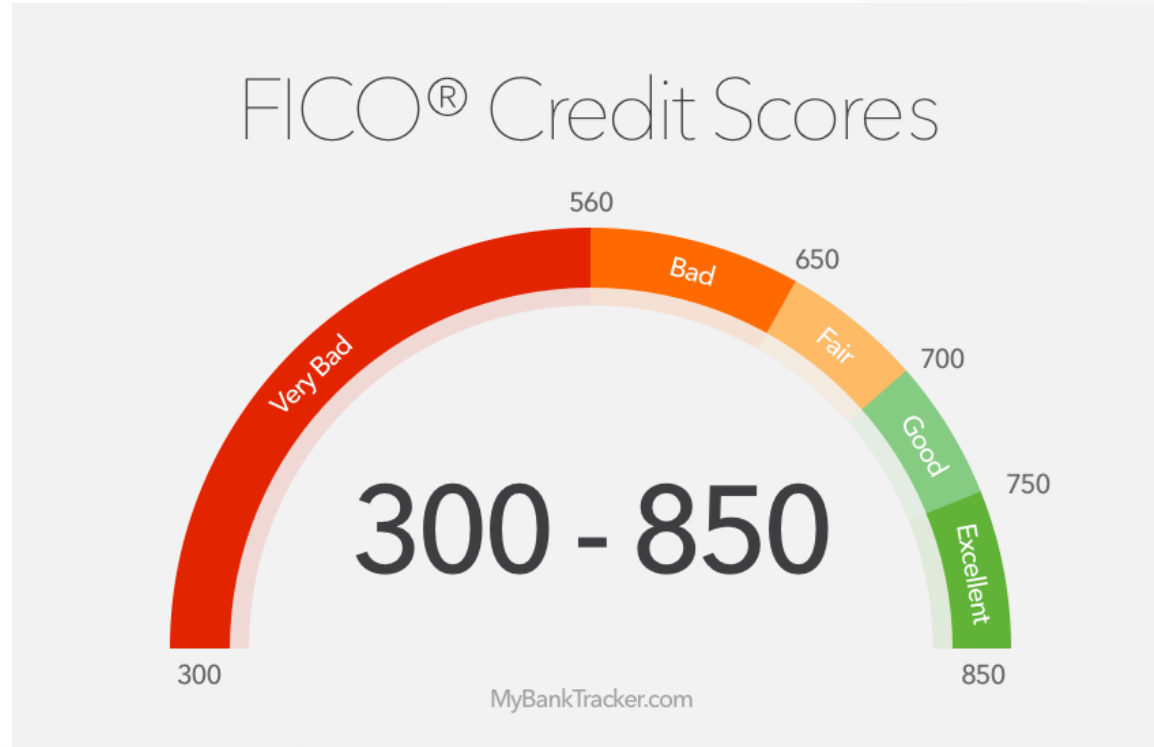
@ Carbon

- How is CARBON using ML for credit scoring and risk prediction
 - DataRobot
 - CARBON ML Architecture & Pipelines overview
- AI Bias vs Human Logical Error
- Conclusion

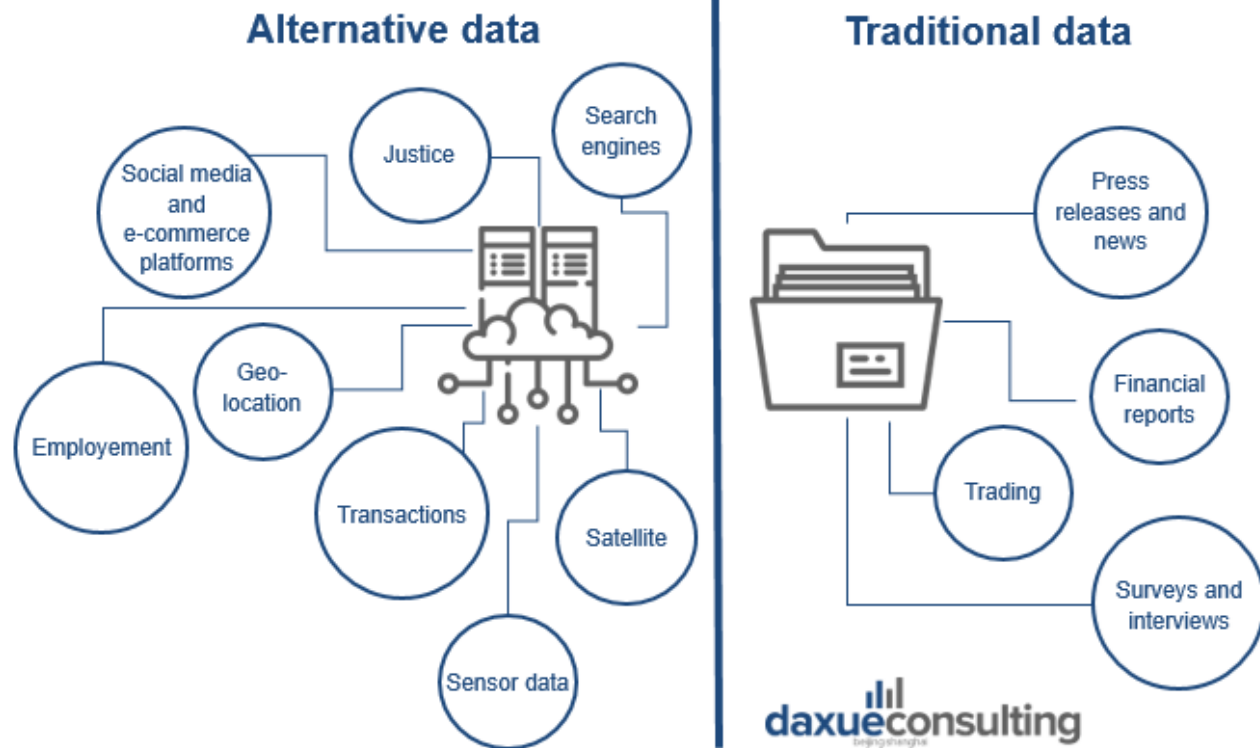
Credit Scoring - Traditional methods



Credit Scoring - Traditional methods



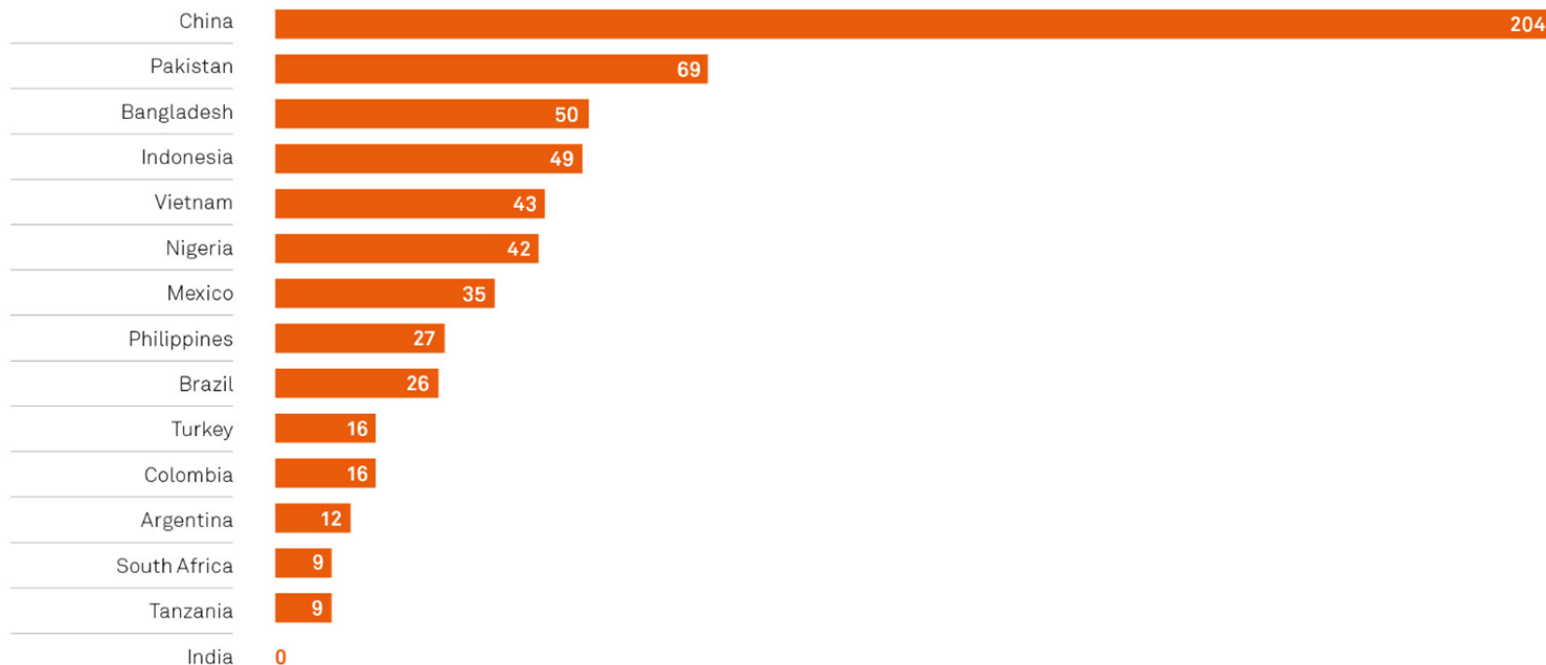
Alternative Data



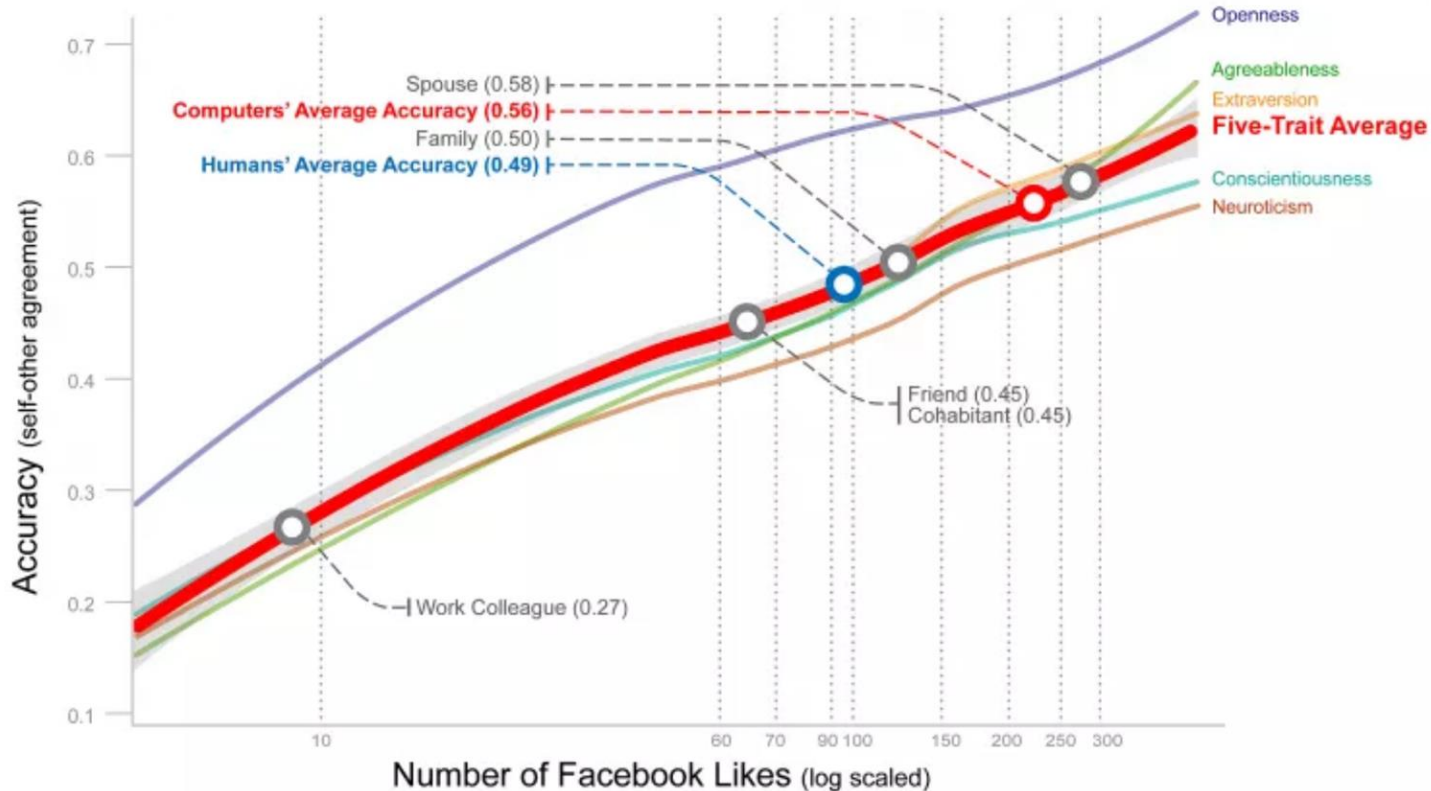
Unbanked population

Tactical Reach Index: Unbanked Populations v Mobile Ownership

Number of people with a phone who outnumber those with a bank account



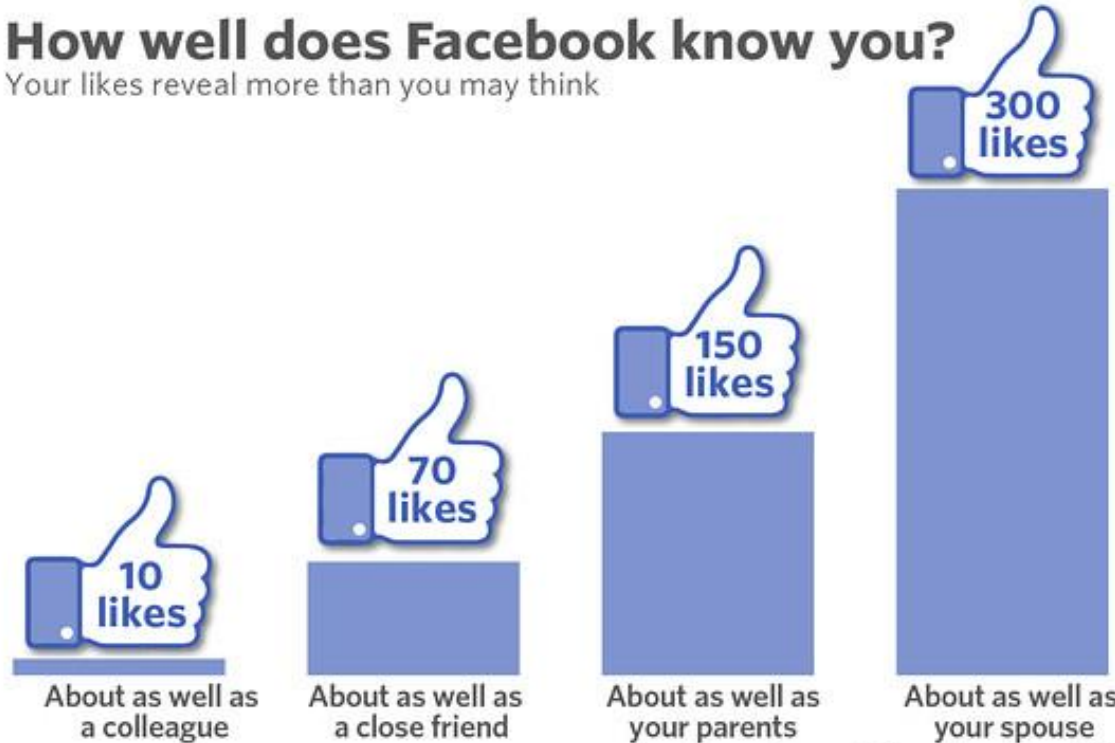
Smartphone and Social Networks : A gold mine?



Smartphone and Social Networks : A gold mine?

How well does Facebook know you?

Your likes reveal more than you may think



Source: University of Cambridge

Methods

- **Payment Default (PD) & Risk Prediction**
- **Algorithms selection overview**

Payment Default (PD) & Risk Prediction

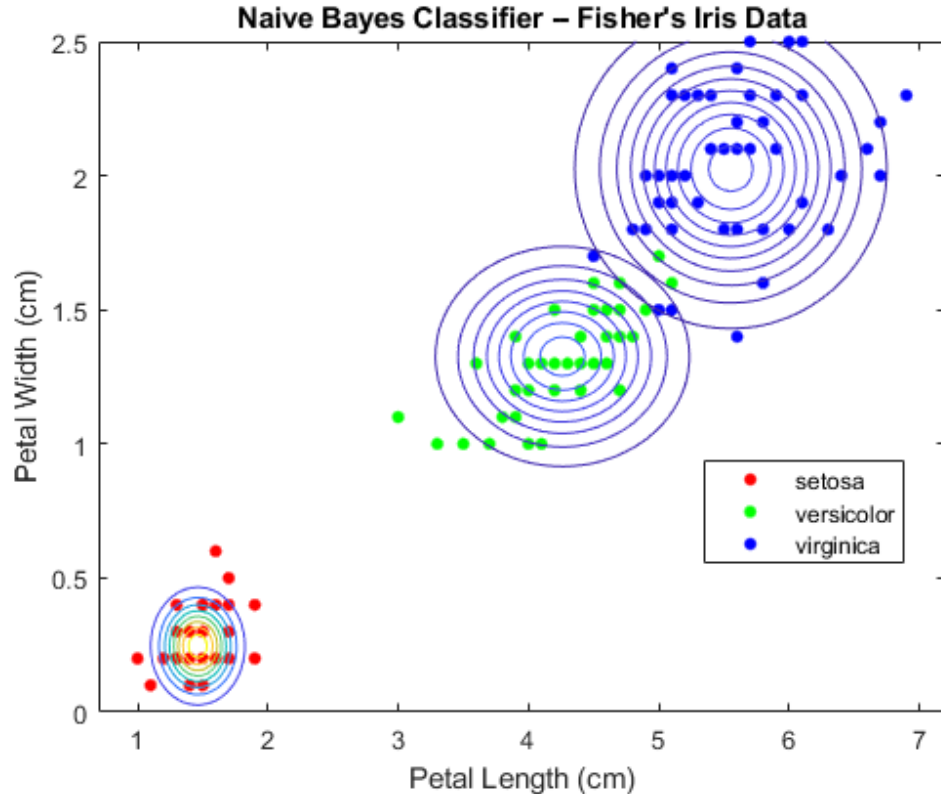
		Impact →				
		Negligible	Minor	Moderate	Significant	Severe
Likelihood ↑	Very Likely	Low Med	Medium	Med Hi	High	High
	Likely	Low	Low Med	Medium	Med Hi	High
	Possible	Low	Low Med	Medium	Med Hi	Med Hi
	Unlikely	Low	Low Med	Low Med	Medium	Med Hi
	Very Unlikely	Low	Low	Low Med	Medium	Medium

Risk Assessment Matrix

Algorithms selection overview

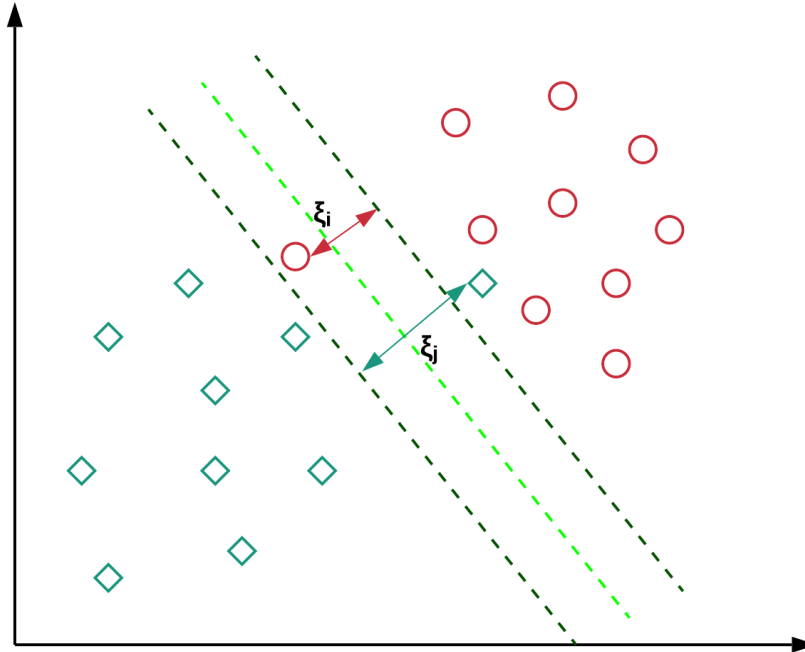
Naive Bayes

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

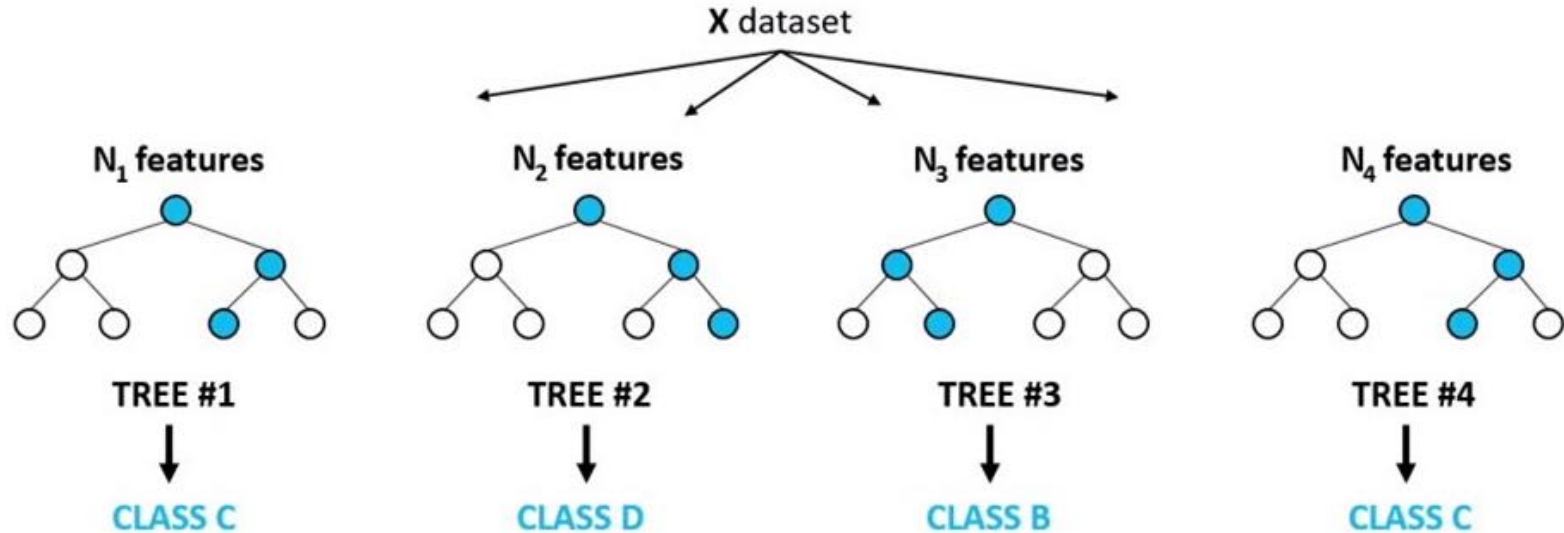


Algorithms selection overview

SVM (Support Vector Machines)



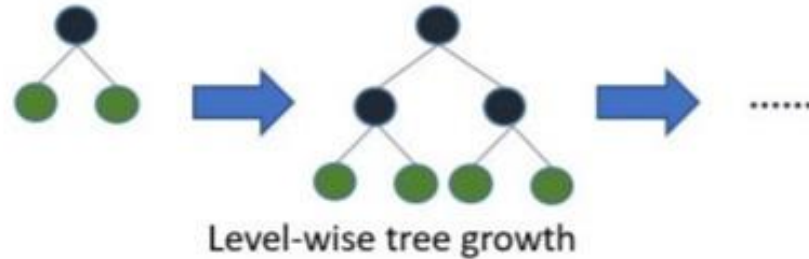
Random Forest



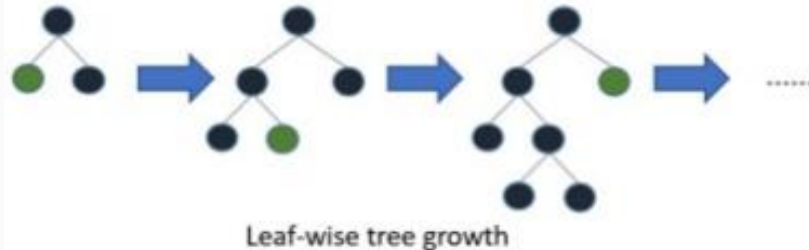
Algorithms selection overview

Extreme and Light Gradient Boosting

XGBoost:

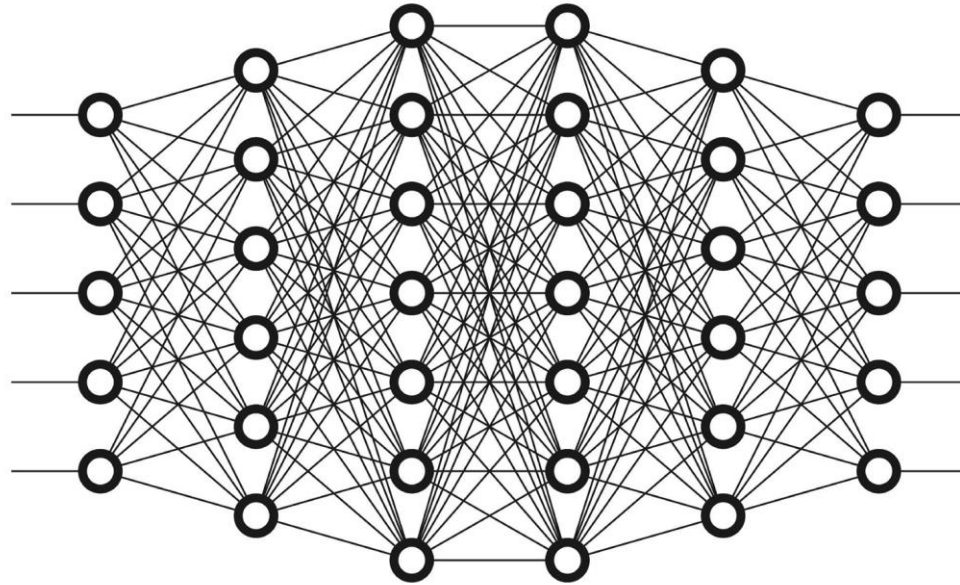


LightGBM:



Algorithms selection overview

**Deep
Learning**



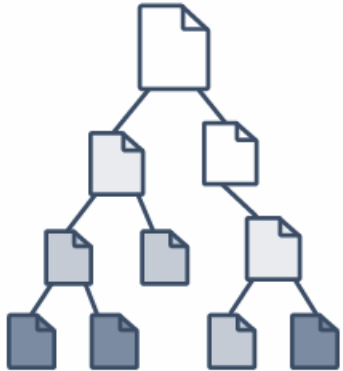
**Why and When XGB is better than
DP?**

Graph Databases

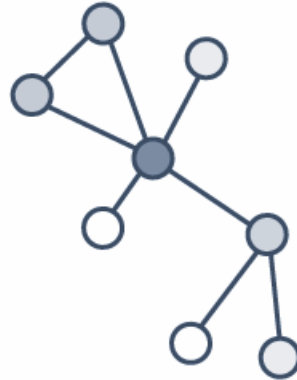
A key to addressing Financial Services challenges.

Types of databases

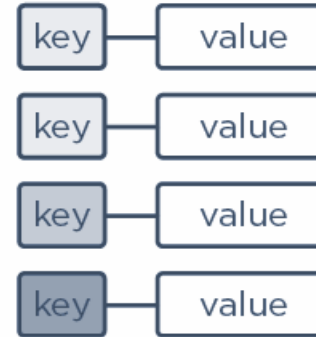
Document



Graph



Key-Value



Wide-column



NO GOOD, NO BAD

Example: Library

NoSQL / Document	SQL / Wide-column	Key-Value	Graph
Book content	Author/Publisher/Date	Book availability	Book usage

Why Graph DB?

Focus on communities and not individuals.

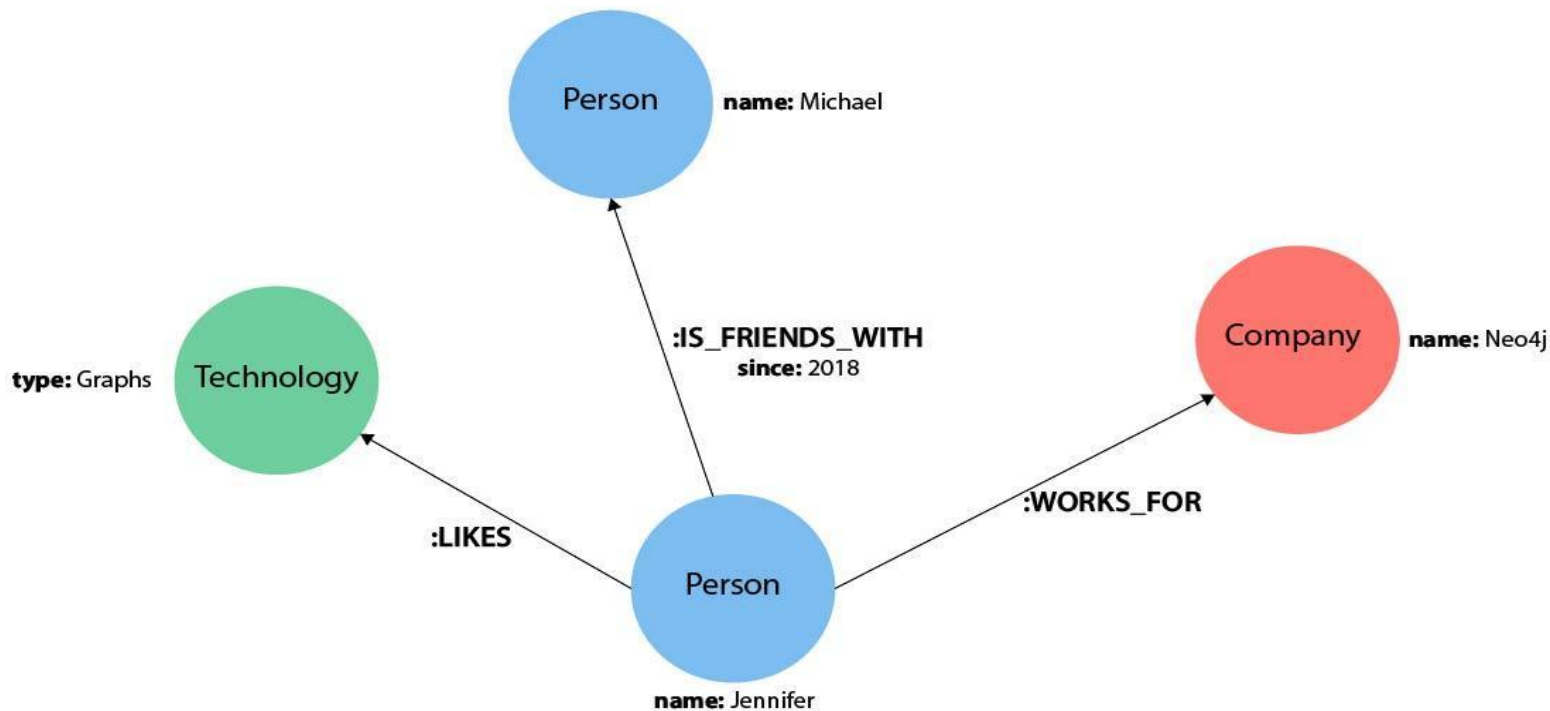
Behaviour is highly influenced by the community.

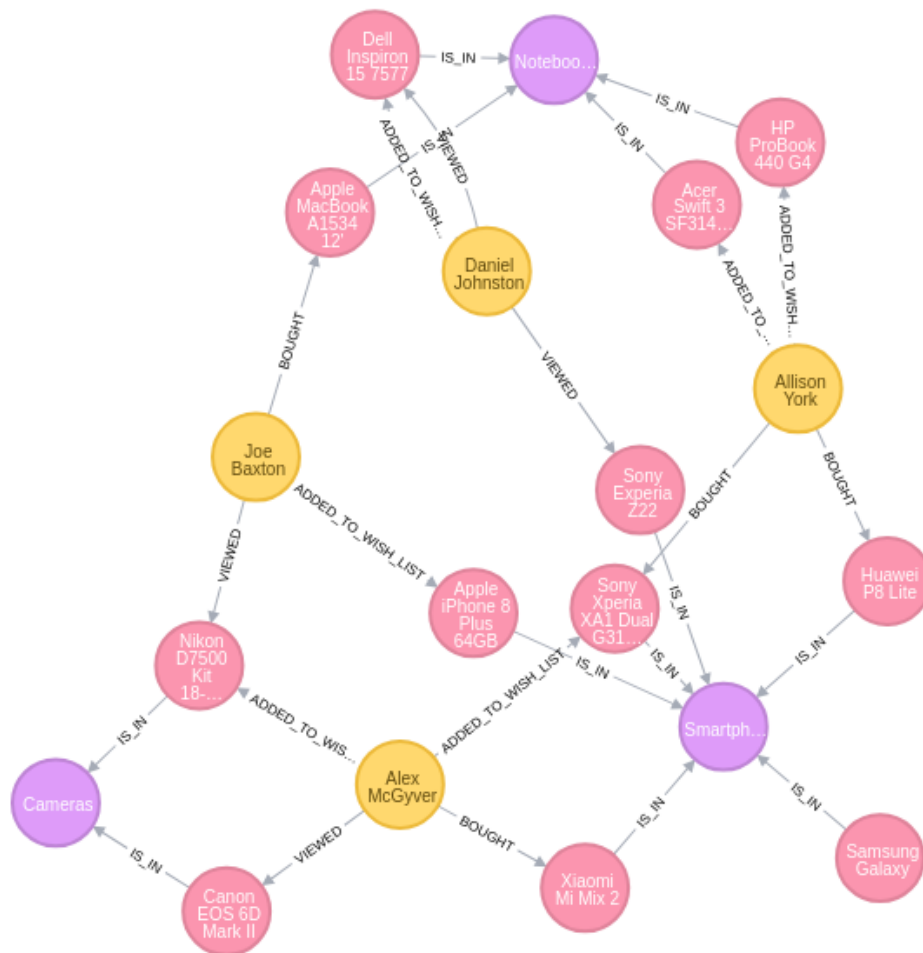
Understanding the customers:

Do they know each other? → Fraud detection

Should they know each other? → Recommendation / Marketing

Neo4j





Cypher

//data stored with this direction

```
CREATE (e:Employee) -[:WORKS_AT]->(c:Company)
```

Cypher



```
//data stored with this direction
```

```
CREATE (e:Employee {name:'Jacob'})-[:WORKS_AT]->(c:Company {name:'Carbon'})
```

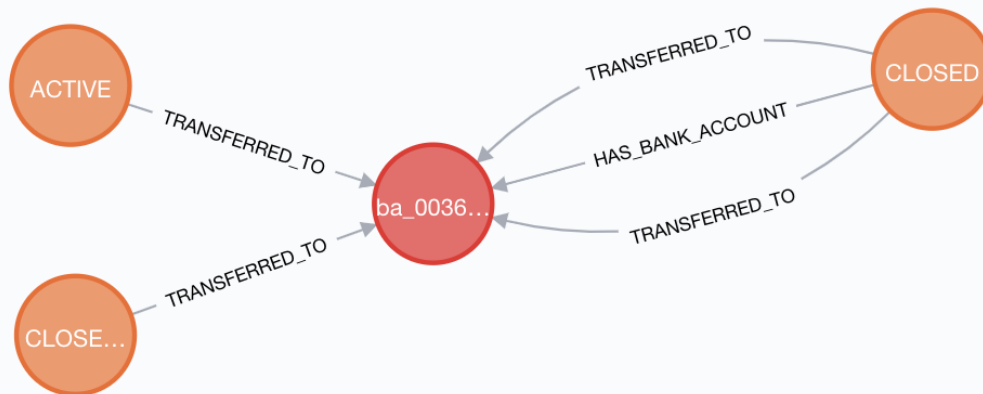
Cypher



```
//retrieve names of Carbon employees  
MATCH (e:Employee) -[:WORKS_AT] -> (c:Company {name:'Carbon'})  
RETURN e.name
```

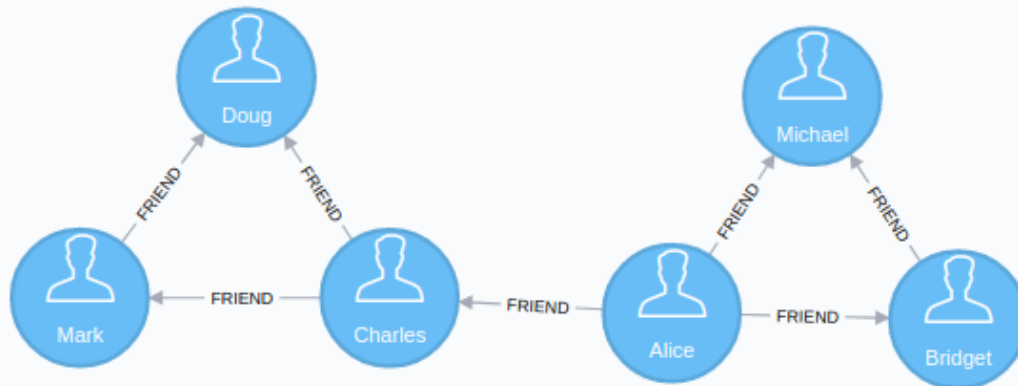
Example: bank transfers

```
MATCH p = (c:client)-->(:bank_account)<--(c2:client)
WHERE c<>c2
RETURN p
```

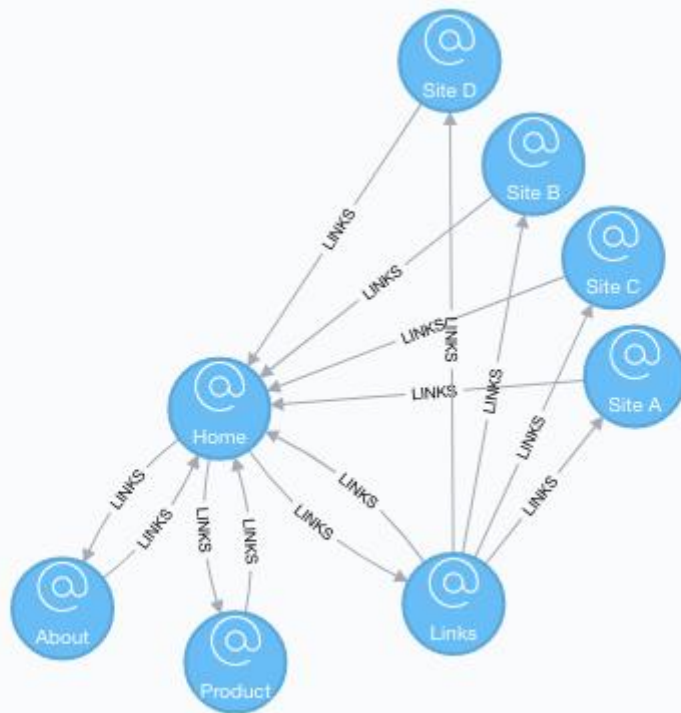


Graph Algorithms

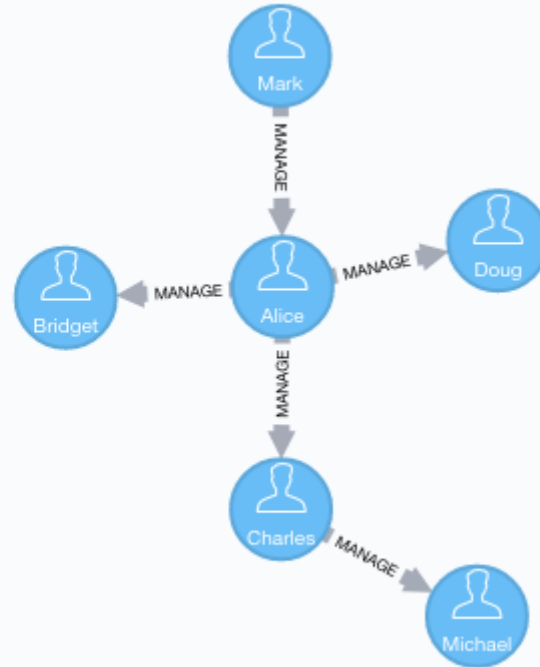
Community detection



Centrality: PageRank



Centrality: Betweenness



Graph DB at Carbon


- **Marketing campaigns**
- **Fraud prevention**

Carbon use cases



- 1. How are we using Machine Learning at CARBON for credit scoring and risk prediction?**



[Leaderboard](#) [Learning Curves](#) [Speed vs Accuracy](#) [Model Comparison](#)[Menu](#) [Search](#) [+ Add New Model](#) [Filter Models](#) [Export](#)☐ Model Name & DescriptionFeature List & Sample Size 

Validation

Metric **AUC** 


Cross Validation

Holdout

**Light Gradient Boosted Trees Classifier with Early Stopping**

Tree-based Algorithm Preprocessing v1

M72 BP58 64.0%

 **RECOMMENDED FOR DEPLOYMENT**DR Reduced Features M55 80.0 % 


0.6811 *

0.6786 *

0.6714

**ENET Blender**

M76 M59+61+55+70+56+...

 **MOST ACCURATE**Multiple Feature Lists 64.0 % 

0.6844

0.6834

0.6751

**AVG Blender**

M74 M55+70+56

Multiple Feature Lists 64.0 % 

0.6848


0.6828

0.6738

**eXtreme Gradient Boosted Trees Classifier with Early Stopping**

Tree-based Algorithm Preprocessing v20

M197 BP68

non-redundant features 64.0 % 

0.6834

0.6817

0.6722

**eXtreme Gradient Boosted Trees Classifier with Early Stopping**

Tree-based Algorithm Preprocessing v20

M58 BP68

final features 64.0 % 

0.6815

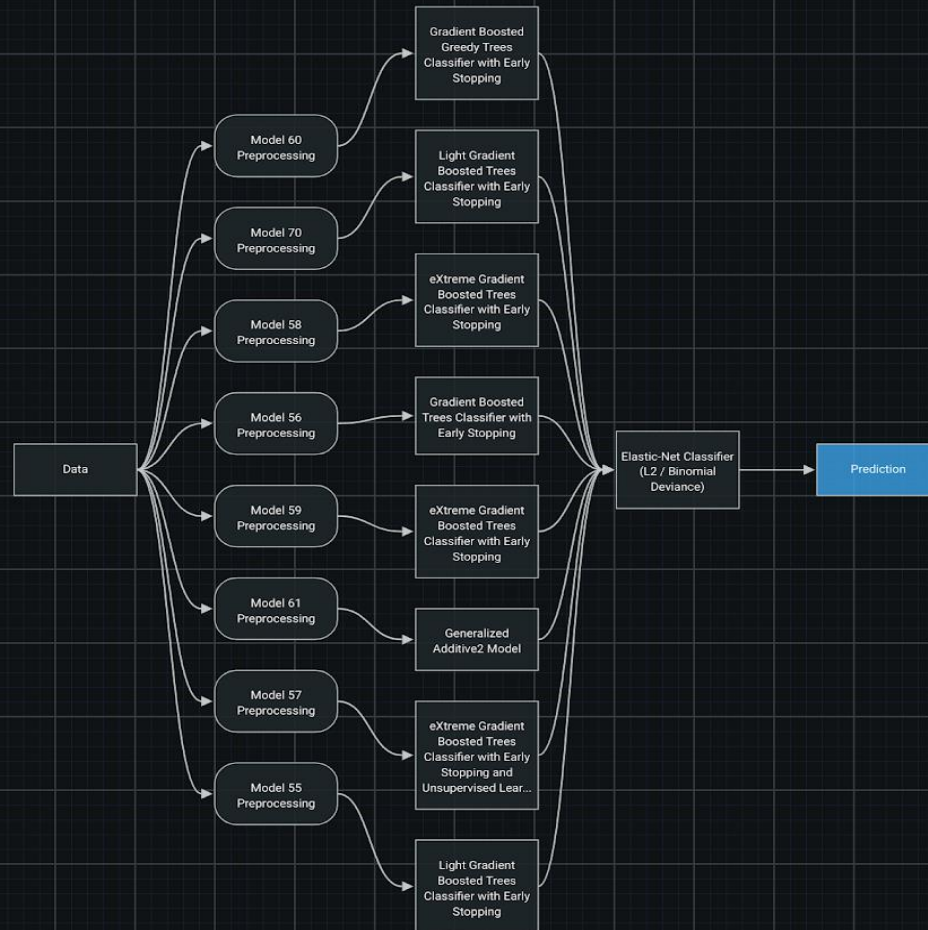
0.6815

0.6724

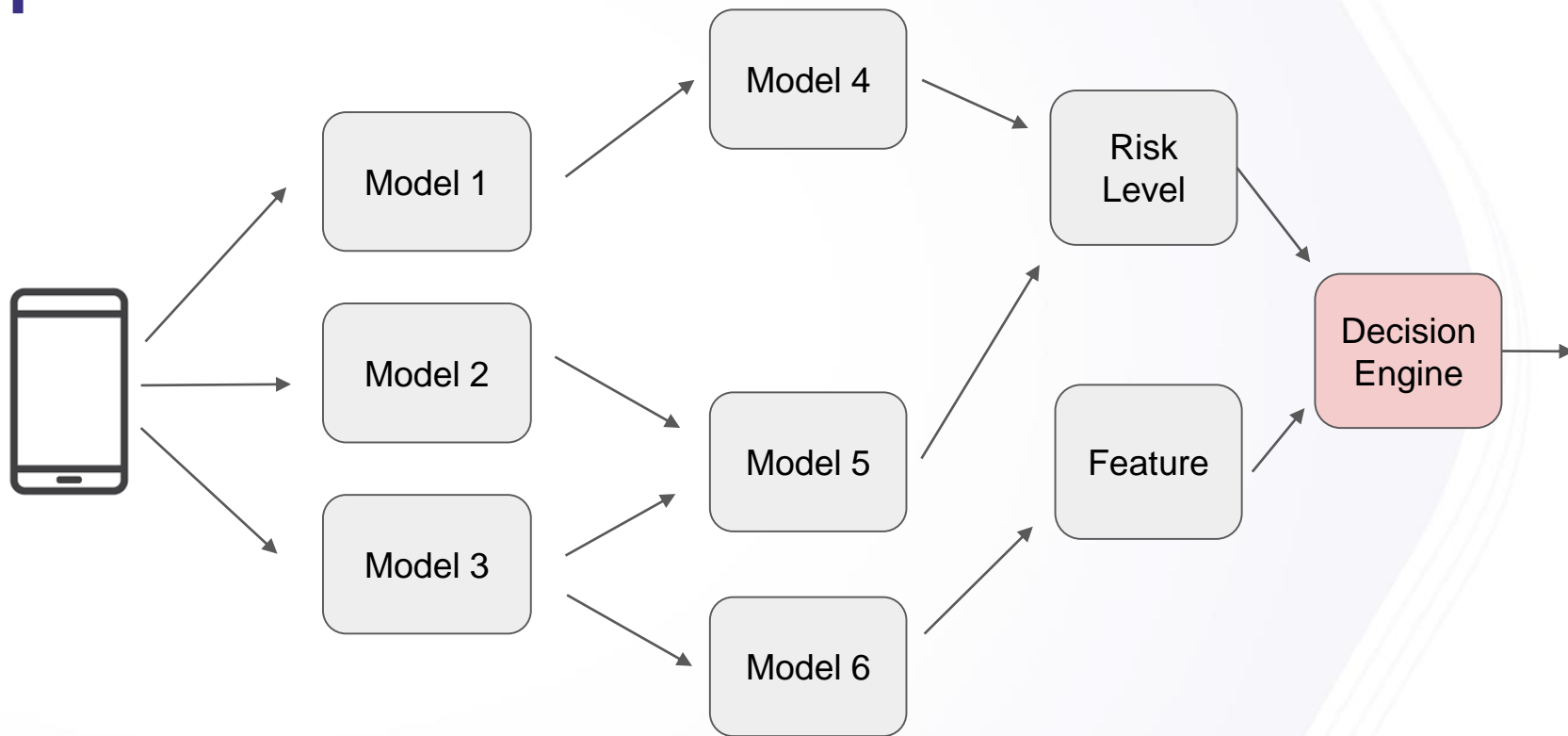
02



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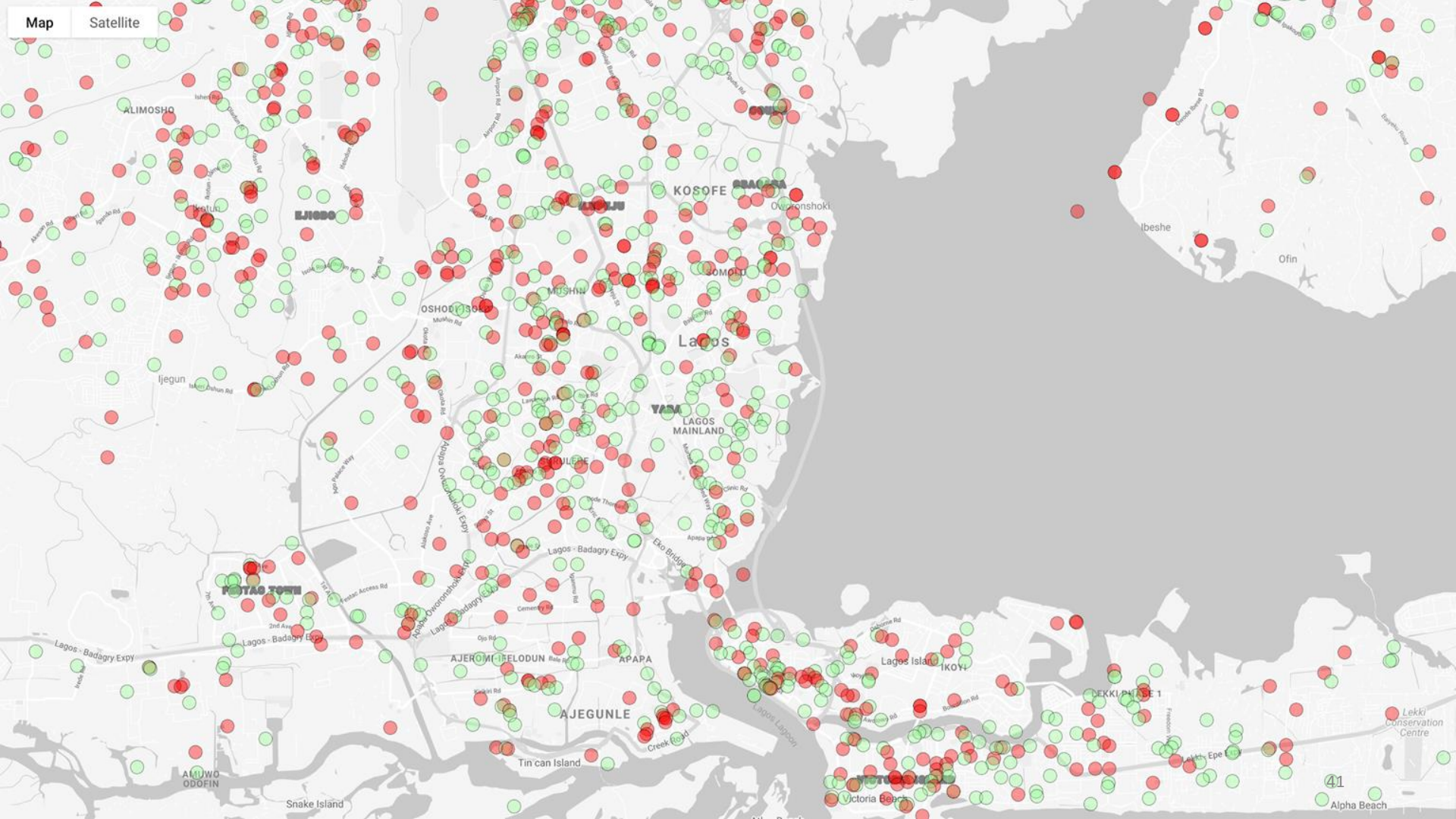
Pipelines Architecture



Why is automation essential ?

Map

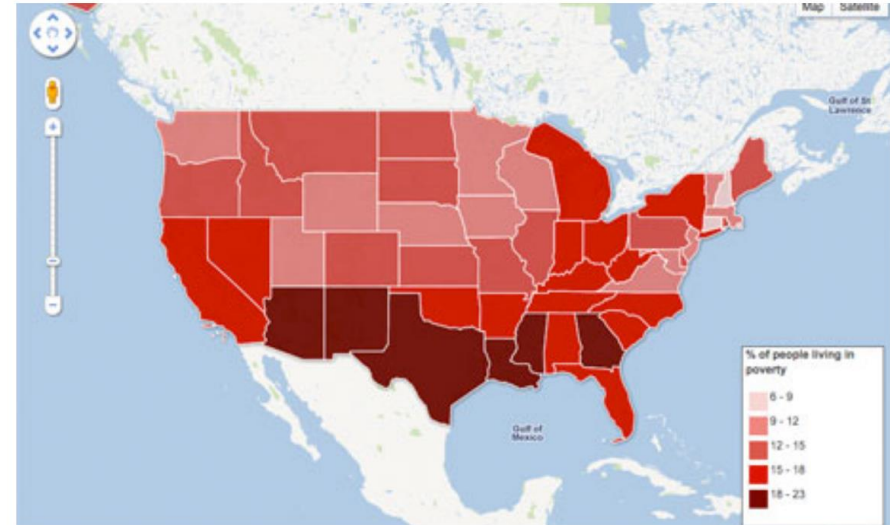
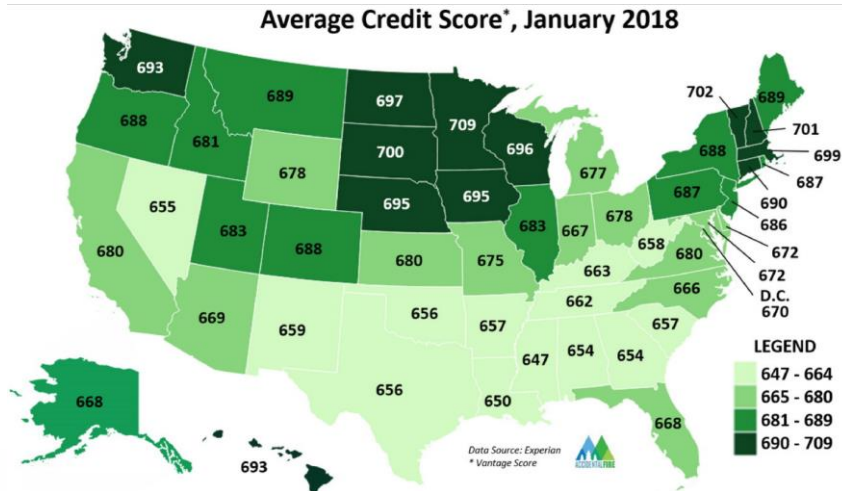
Satellite



7,344 GB
?

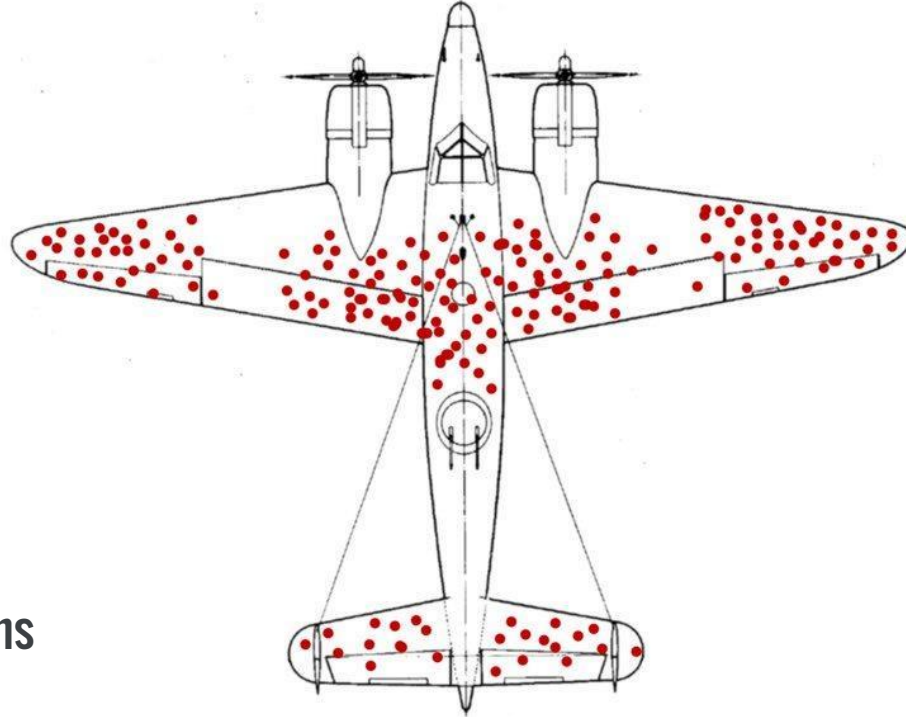
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AI Bias vs Human Logical Error



US poverty interactive map. [Click image to explore it](#)

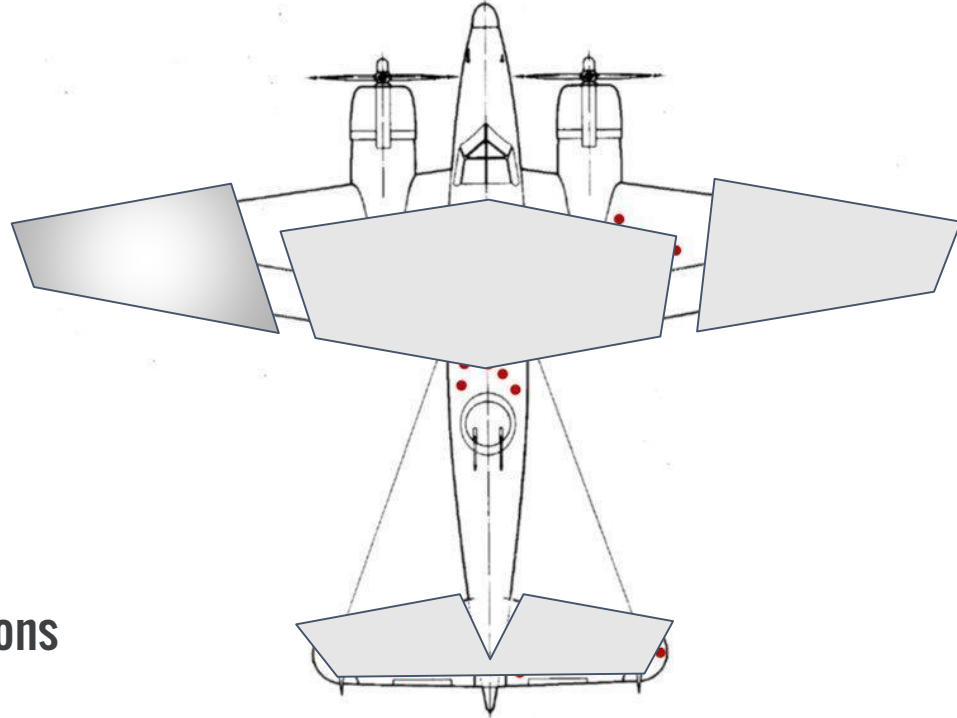
AI Bias vs Human Logical Error



Planes that returned from missions

AI Bias vs Human Logical Error

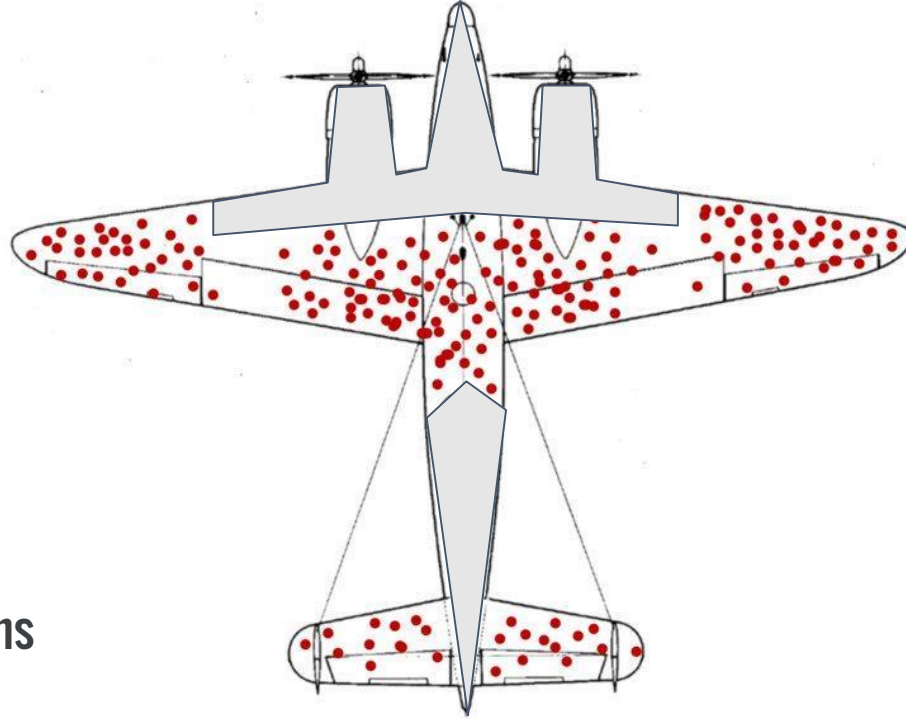
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Planes that returned from missions

AI Bias vs Human Logical Error

=



Planes that returned from missions

Thank You